Distributed Big Data Analytics
Efficient First Order Inductive Learner on Spark

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University of Bonn, 2017

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Definition 7. A tuple satisfies a learning rule if it satisfies one of the Horn clauses of this rule.
For every relation a set of the $\oplus$tuples which belong to this relation is given. For a target relation a set of $\oplus$tuples is also given. A set of the $\ominus$tuples not belonging to the target relation may be given. The statement is introduced: if some tuple is not included in set $\oplus$tuples then it is $\ominus$tuple.

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Problem statement: Using Spark framework realize FOIL to find a learning rule as a set of Horn clauses for the target relation that consistent with given positive examples and not cover any given negative examples.

Approach

Foil algorithm is realized using Scala in Spark framework.

1	Let Pred be the predicate to be learned
2	Let Pos be the positive examples
3	Until Pos is empty do:
4	Let Neg be the negative examples
5	Set Body to empty
6	Let Old be those variables used in Pred
7	CallLearnClauseBody
8	Add Pred $\leftarrow$ Body to the rule
9	Remove from Pos all examples that satisfy the Body
7a	Procedure CallLearnClauseBody
7b	Until Neg is empty do:
7c	For each predicate-name P
7d	For each variabilization L of P
7e	Compute information gain of L and its negation
7f	Select literal L with most information gain
7g	Conjoin L to Body
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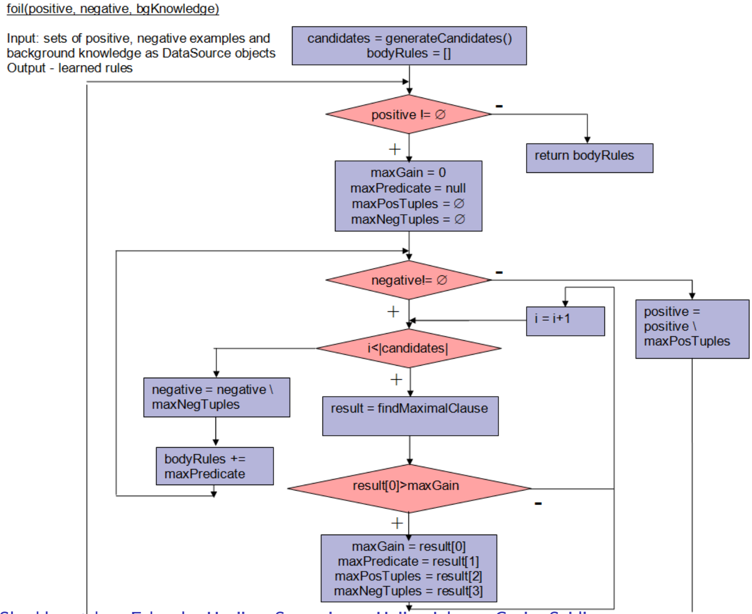
To select literal with greatest positive gain:

$$gain(L_i) = n_i^{\oplus\oplus} \cdot (I(T_i) - I(T_{i+1})), \quad I(T_i) = -\log_2(n_i^{\oplus}/(n_i^{\oplus} + n_i^{\ominus})), \qquad (2)$$

$n_i^{\oplus}$ — a number of $\oplus$tuples in T_i, $n_i^{\ominus}$ — a number of $\ominus$tuples in T_i,
$n_i^{\oplus\oplus}$ — a number of the $\oplus$tuples in T_i represented by one or more tuples in T_{i+1}.

Implementation



Evaluation

Evaluation metrics: $\rho_k(A_1, A_2) = |n_k(A_1) - n_k(A_2)|,\ k = 1, 2, 3.$

Indicators: $n_1(A) = \frac{n^{\oplus}_{\text{covered}}(A)}{n^{\oplus}_{\text{given}}},\ n_2(A) = \frac{n^{\ominus}_{\text{covered}}(A)}{n^{\ominus}_{\text{given}}},\ n_3(A) = \mathrm{runtime}(A).$

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Experiment 1. (a), results: $daughter(X_1, X_2) \leftarrow female(X_1) parent(X_2, X_1)$; covered $\oplus$ examples: (Emily, Tom), (Mary, Ann); covered $\ominus$ examples: $\emptyset$.

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Experiment 2. (b), results: $daughter(X_1, X_2) \leftarrow female(X_1) parent(X_2, X_1)$;
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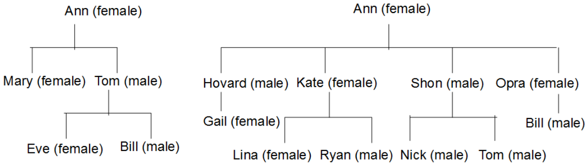
Experiment 3. (b), results: $son(X_1, X_2) \leftarrow male(X_1) parent(X_2, X_1)$; covered $\oplus$ examples: (Ryan, Uve), (Bill, Opra), (Hovard, Ann), (Nick, Kate), (Uve, Ann), (Tom, Uve); covered $\ominus$ examples: $\emptyset$.



(a) (b)

Table 2. Efficiency indicators.

No Experiment	Proportion of covered $\oplus$(%) examples	Proportion of covered $\ominus$ examples (%)	Running time (sec)
1	100	0	0.188
2	100	0	0.207
3	100	0	0.200

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2. Evaluation of the application efficiency compared to other implementations of the Foil algorithm.

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1. The extension of our general skills on applications development using the Spark framework and the Scala programming language;
2. Gaining experience in project testing and selection of evaluation datasets.
3. Getting deeper understanding of how and when to apply distributed means of data processing.

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